

Machine Learning HW 4 Report

0516215 林亮穎

1. Forward-propagate code

```
def forward_propagate(X, theta1, theta2):
    m = X.shape[0]
    X = np.matrix(X)

    #Write codes here
    a1 = np.concatenate((np.ones((m, 1), dtype=float), X), axis=1)      # 5000x401
    z2 = np.dot(a1, theta1.T)      # 5000x401 * 401x10 = 5000x10
    a2 = np.concatenate((np.ones((m, 1), dtype=float), sigmoid(z2)), axis=1) # 5000x11
    z3 = np.dot(a2, theta2.T)      # 5000x11 * 11x10 = 5000x10
    h = sigmoid(z3)               # 5000x10

    return a1, z2, a2, z3, h
```

2. Back-propagate code

```
93 def backprop(params, input_size, hidden_size, num_labels, X, y, learning_rate):
94     m = X.shape[0] #5000 testcases
95
96     #Write codes here
97
98     theta1 = np.matrix(np.reshape(params[:hidden_size * (input_size + 1)], (hidden_size, (input_size + 1))))
99     theta2 = np.matrix(np.reshape(params[hidden_size * (input_size + 1):], (num_labels, (hidden_size + 1))))
100     nabla1 = np.zeros((hidden_size, input_size+1)) # 10x401
101     nabla2 = np.zeros((num_labels, hidden_size+1)) # 10x11
102
103     for i in range(0, m):
104
105         # STEP1: Forward Propagation
106         # a1, z2, a2, z3, h = forward_propagate(X, theta1, theta2)
107         tmp = X[i,:]
108         tmp.shape
109         a1 = np.c_[np.ones((1,)), X[i, :]]      # 1x401
110         z2 = np.dot(a1, theta1.T)               # 1x401 * 401x10 = 1x10
111         a2 = np.c_[np.ones((1,)), sigmoid(z2)]  # 1x11
112         z3 = np.dot(a2, theta2.T)               # 1x11 * 11x10 = 1x10
113         h = sigmoid(z3)                        # 1x10
114
115         # STEP2: Calculate delta3
116         delta3 = h - y[i, :]                   # 1x10
117         delta3 = delta3.T                      # 10x1
118         delta3.shape
119
120         #STEP3: Calculate delta2
121         # delta2 = np.dot((theta2[:,1:]).T, delta3) * sigmoid_gradient(z2).T # 10x10 * 10x1 = 10x1
122         delta2 = np.multiply(np.dot((theta2[:,1:]).T, delta3), sigmoid_gradient(z2).T)
123         # delta2 = np.dot((theta2[:,1:]).T, delta3) # 10x10 * 10x1 = 10x1
124
125         #STEP4: Accumulate the gradient
126         nabla1 = nabla1 + np.dot(delta2, a1)    # 10x1 * 1x401 = 10x401
127         nabla2 = nabla2 + np.dot(delta3, a2)    # 10x1 * 1x11 = 10x11
128
129
130
```

```

130
131 # STEP5: Obtain the gradient
132 grad1 = (1.0/m) * nabla1 # 10x401
133 grad2 = (1.0/m) * nabla2 # 10x11
134
135 lambda_ = 1
136 grad1[:, 1:] = grad1[:, 1:] + (lambda_/m) * theta1[:, 1:] # do not regularize bias
137 grad2[:, 1:] = grad2[:, 1:] + (lambda_/m) * theta2[:, 1:]
138
139
140 grad = np.hstack((grad1.ravel(), grad2.ravel()))
141
142 params_trained = np.hstack((theta1.flatten(), theta2.flatten()))
143 J = cost(params_trained, input_size, hidden_size, num_labels, X, y, learning_rate)
144
145 return J, grad

```

3. Result accuracy

```
accuracy = 97.34%
```